Regents Junior Faculty Fellowship

Ryan Giordano

I propose to spend the summer of 2024 working on two collaborative research projects. The first, "neural network classifiers for Bayesian posteriors," promises to introduce a completely new set of Bayesian inference techniques based on ideas from simulation–based inference. The second, "black–box computable diagnostic weights for survey sampling," will bring a much–needed set of diagnostic tools to the vast majority of modern applied survey sampling. These two projects are different in scope — the first represents ground–breaking methodological research, and the second an application of my existing research to an urgent applied problem — but each rests on and contributes to my existing work and expertise on approximate Bayesian computation and sensitivity analysis.

Neural network classifiers for Bayesian posteriors

Bayesian statistical techniques are a conceptually powerful set of tools for representing and quantifying uncertainty, and are increasingly popular across the physical and social sciences. Often, a statistical analysis involves a single quantity of interest, such as the effect of a policy intervention [Meager, 2019], the type of an astronomical object [Regier et al., 2019], the outcome of an election [Gelman and Heidemanns, 2020], or the identity of an ancestral genetic population [Pritchard et al., 2000]. Bayesian statistics is able to propagate uncertainty from any unknown latent modeling quantities to the final estimate. But this conceptual strength is a computational weakness, since even approximately accounting for a large number of latent quantities is computationally intensive. Bayesian estimates often take hours to days to compute, and it is of considerable interest to develop computationally efficient, approximate Bayesian procedures [Blei et al., 2017, AABI, 2024].

In consultation with a staff scientist at LBNL, I have recently developed a new approach to Bayesian inference based on neural network classifiers (NNC). The idea is derived from a technique for point estimation in simulation–based inference (SBI),[1] a technique I will refer to as SBI-NNC [Cranmer et al., 2020]. Rather than learning a likelihood directly, SBI-NNC exploits the fact that optimal neural network classifiers learn likelihood ratios. I have shown that a variant of the SBI-NNC trick can be applied to learn Bayesian marginals without having to learn the distribution of all the latent variables, at the cost of training a NNC on a single classification task. I will refer to my technique as Bayes–NNC.

Both classical Bayesian procedures and the existing SBI-NNC trick are difficult to validate in practice, due to the lack of a computable ground truth. Amazingly, Bayes–NNC does not suffer from this shortcoming, and its accuracy is readily testable using simulation–based calibration (SBC) [Talts et al., 2018]. Put together, Bayes–NNC and SBC offer a way to learn Bayesian posterior densities of low–dimensional quantities of interest with strong, computable statistical accuracy guarantees. Interestingly, SBC is well–known but rarely used in practice, since it is typically computationally prohibitive to compute the posterior at many different datapoints. However, Bayes–NNC learns the posterior for many datasets simultaneously, permitting efficient use of SBC in practice.

To my knowledge, there are no existing Bayesian techniques that offer the advantages of Bayes-NNC and SBC. Bayesian approaches to simulation–based inference are not new, but

[1] That is, inference in problems without a tractable likelihood function.

existing techniques are built on high–dimensional density approximation, such as normalizing flows [Cranmer et al., 2020, Papamakarios et al., 2021]. As with other approximate inference techniques, this set of tools approximates the entire posterior, even when only a low–dimensional marginal is of interest. To the best of my (and my LBNL collaborator's) knowledge, Bayes–NNC is new, and offers a distinct and advantageous set of computational tradeoffs relative to existing Bayesian inference methods.

Black–box computable diagnostic weights for survey sampling

Most modern surveys — such as polling about the upcoming presidental election — must overcome the fact that their sampled population is different from the target population [Gelman, 2007]. For example, the set of people responding to an internet survey about political preferences is likely to differ systematically from the full population of voters, and it is extremely useful to be able to check that the re-weighting is accurate, for example by checking that key demographic variables are balanced by the re-weighting [Li et al., 2018, B. et al., 2021]. Unfortunately, the most accurate and most commonly used statistical procedures for inferring the polling responses of rare demographic groups are nonlinear, and so do not readily admit diagnostic weights [Gelman, 1997, 2007].

In collaboration with a UC Berkeley professor of public policy, I have shown that one can compute "local diagnoistic weights" for non–linear statistical procedure, provided a much–needed diagnostic that is currently unavailable. The local weights I derive are closely related to the classical "influence function" of robust statistics [Mises, 1947, Hampel et al., 1986, Giordano et al., 2019]. Though the influence function is well–studied in the frequentist literature, it has been relatively neglected in the Bayesian literature (with my own recent work, Giordano and Broderick [2023], being a notable exception).

Importantly, the local weights can be automatically computed with a small library built on top of existing open–source software which is commonly used for survey analysis [Lopez-Martin et al., 2022]. I have already implemented a similar package for a different style of sensitivity analysis [Broderick et al., 2020, Giordano, 2024], and we expect to be able to release open–source software relatively quickly.

References

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R. Giordano, W. Stephenson, R. Liu, M. I. Jordan, and T. Broderick. A Swiss army infinitesimal jackknife. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pages 1139–1147. PMLR, 2019.

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R. Meager. Understanding the average impact of microcredit expansions: A Bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics*, 11(1):57–91, 2019.

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J. Regier, K. Fischer, K. Pamnany, A. Noack, J. Revels, M. Lam, S. Howard, R. Giordano, D. Schlegel, and J. McAuliffe. Cataloging the visible universe through Bayesian inference in Julia at petascale. *Journal of Parallel and Distributed Computing*, 127:89–104, 2019.

S. Talts, M. Betancourt, D. Simpson, A. Vehtari, and A. Gelman. Validating Bayesian inference algorithms with simulation-based calibration. *arXiv preprint arXiv:1804.06788*, 2018.

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Professional Experience

University of California Berkeley, CA USA — 2023–present
Assistant professor of statistics.

Massachusetts Institute of Technology, Cambridge, MA USA — 2019–2023
Department of EECS, Laboratory for Information & Decision Systems
Postdoctoral Research Fellow.

Google Inc., Mountain View, CA USA — 2009–2013
Senior Engineer, Quantitative Analysis

Macquarie Group, London, UK — 2008
Risk Management Intern

United States Peace Corps, Kokshetau, KZ — 2004–2006
Education Volunteer, successful completion of service

Hewlett-Packard, Boise, ID — 2002–2004
Lifetest Coordinator and Reliability Engineer

Education

University of California Berkeley, CA USA — 2013–2019
Ph.D., Statistics. Advisors: M. I. Jordan, J. McAuliffe, T. Broderick
Thesis: *On the Local Sensitivity of M-Estimation: Bayesian and Frequentist Applications*

London School of Economics, London, UK — 2006–2008
MSc., Econometrics.

University of Illinois Urbana-Champaign, IL, USA — 1997–2002
BA., Mathematics.
BS., Theoretical and Applied Mechanics.

Honors and Awards

Selected for the Nov 5th 2021 Gary Chamberlain Online Seminar in Econometrics (2021)
Notable Paper Award, Artificial Intelligence and Statistics (AISTATS) (2019)
Travel Award, Artificial Intelligence and Statistics (AISTATS) (2019)
Travel Award, Bayesian Nonparametrics Conference (2019)
Student Paper Award, ASA Section on Bayesian Statistical Science (2018)
Travel Award, International Society for Bayesian Analysis (ISBA) (2018)
Berkeley Institute for Data Science Fellow (2017–19)
Junior Travel Support Grant, International Society for Bayesian Analysis (ISBA) Bayes Comp (2016)
Spotlight Paper, Neural Information Processing Systems (NeurIPS) (2015)
Outstanding Graduate Student Instructor Award (2015)
Travel Award, Neural Information Processing Systems Workshop on Variational Inference (2014)
Hertz Foundation Graduate Fellowship Finalist (2014)
Google Operating Committee Award (2010)
Advanced-high speaker of Russian in Peace Corps Aptitude Test (2006)
Advanced-mid speaker of Kazakh in Peace Corps Aptitude Test (2006)
Selected as a Peace Corps "Success Story" for a congressional report (2005)
Best Project, Undergraduate Mechanics Research Conference (2002)
Best Presentation, Undergraduate Mechanics Research Conference (2002)
Seely, Sinclair, Stippes, TAM Merit Scholarships (1998–2002)

Professional Service

University of California, Berkeley, Statistics Department

Faculty service

- Neyman seminar organizer 2023–2024
- Gaussian processes reading group co–organizer 2023–2024
- Statistics course website modernization pilot program 2023–2024

Student leadership

- Diversity Taskforce Member 2018–2019
- Graduate Student Mentor 2017–2019
- Diversity Committee Member 2017
- Co-organizer of the Gender and Diversity Roundtable 2016–2018
- Student Seminar Committee Member 2014–2017

Universty of Illinois, Urbana-Champaign, Engineering Mechanics Department

- President, Student Society for Experimental Mechanics 2000–2002
- Organizer, Free University Opera for Engineering Students 2001–2002

Journal Reviewing

- Econometrics Journal
- Bayesian Analysis
- Journal of Machine Learning Research
- JRSS-B

Conference Reviewing

- Advances in Neural Information Processing Systems (NeurIPS)
- International Conference on Machine Learning (ICML)
- International Conference on Artificial Intelligence and Statistics (AISTATS)
- Advances in Approximate Inference (NeurIPS-adjacent workshop)
- I Can't Believe It's Not Better (NeurIPS workshop)

Teaching

University of California, Berkeley, CA, USA

- Professor, STAT151A Linear models Spring 2024

University of California, Berkeley, CA, USA

- Teaching Assistant, STAT215 Applied Statistics (Graduate-level) Fall 2014

Prison University Project, San Quentin State Prison, CA, USA

- Volunteer math teacher Fall 2015, Spring 2016, Fall 2017

Kokshetau Elementary School #3, Kokshetau, Akhmola, Kazakhstan

- Elementary school teacher of mathematics and English as a second language 2004–2006

University of Illinois, Urbana-Champaign, IL, USA

- Teaching Assistant, Mechanics of Materials Lab Fall 1999
- Teaching Assistant, Introduction to Statics Spring 1999